Anxiety and Learning in Dynamic and Static Clock Game Experiments

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Abstract

In clock games, agents receive differently-timed private signals when an asset value is above its fundamental. The price crashes to the fundamental when K of N agents have decided to sell. If selling decisions are private, bubbles can be sustained because people delay selling, after receiving signals, knowing that others will delay too. Our results replicate the main features of the one previous experimental study of clock game (in two subject pools): Selling delays are shorter than predicted, but converge toward equilibrium predictions over repeated trials. We also find that delays are shorter in a dynamic game in which selling decisions unfold over time, compared to a static equivalent in which subjects precommit to selling decisions. A model of learning with growing anxiety after signal arrival can reproduce the empirical observations of shorter-than-predicted delay, smaller delay after later signal arrival, and shorter delays in dynamic games.

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JEL codes C92, C72, D03

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1. Introduction

Many economic choices consist of whether to accept a sure payoff or to wait for a risky payoff that is potentially larger, where the risky payoffs from waiting depend on choices of others. Examples include timing stock market trades, adopting new technology, optimal timing of entry or product launches to new growing markets, and bank runs [1, 2, 3, 4, 5, 6]. For journalists and (sometimes) academics, a similar tradeoff exists between publishing quickly or waiting to gather better information. Waiting can improve the quality of an article but creates an increasing risk of being scooped.

Our experimental study explores a stylized economic environment with costs and benefits for waiting or taking an immediate action. These clock games were introduced by Brunnermeier and Morgan [7, 8] (henceforth BM) to create interesting timing decisions in the presence of the trade-off between rewards from waiting versus risk of preemption.

Clock games are useful for several reasons. Under simplifying conditions, they can be modeled formally. Optimal equilibrium behavior has a surprisingly simple closed-form optimal strategy (a timing decision). This sharp prediction about equilibrium behavior makes it easy to detect any deviation from the optimal strategy and then invites productive speculation about why deviations occur, in a way that can be tested with more experiments. Clock games also provide a general paradigm to study psychological processes related to strategic reasoning of what others will do, managing real-time emotions (e.g., anxiety and stress[1]), and revising a strategy based on feedback (learning based on reinforcement and regret from exiting too early or waiting too long).

This study makes three contributions: (1) we replicate the basic result of BM (despite substantial changes in procedure); (2) we test strategic equivalence of dynamic and static implementations of the clock game; and (3) we provide a model of subject learning during the experiment.

Our paper can be evaluated as an extensional part of a package with the original BM paper. BM introduced an interesting paradigm and provided some experimental data comparing response of behavior to some structural variables. They tested theoretical predictions about timing decisions. Some parts of the theory were not sharply supported by the data.

Our paper picks up where BM left off. We introduce a slightly different experimental paradigm, in which human subjects play against computerized rivals who play an equilibrium strategy. We also compare a real-time dynamic game with a strategically equivalent "static" form of the clock game in which agents commit to strategies (conditional on private information). The static game creates more data (it eliminates censoring of data, for reasons that will become apparent) and also creates an interesting comparison between strategically-equivalent

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[1]In psychology, several studies have used a "balloon task" (BART) which is related to a clock game [9, 10]. In the balloon task a person can accept a certain payoff or choose to inflate the balloon. Inflating the balloon has a chance of increasing the certain payoff, but inflating also has a risk of bursting the balloon, leaving a game-ending payoff of zero. Balloon games are thought to be measures of impulsivity and self-control, akin to repeated use by drug addicts and other challenges to self-control [11]. The clock game is a social balloon task, in which the time at which the balloon bursts is determined the actions of all players. A synthesis of the two types of tasks might prove useful to distinguish private impulse control and social effects.

dynamic and static forms. We find that there is a sharp difference in play in the two versions of the game. We provide some evidence that this difference might be interpreted as "anxiety" agents feel about uncertainty resolution in the dynamic game. We also study the process of learning and see how individuals adapt their strategy over time.

2. Theory

This section describes the dynamic clock game in detail. This is the original form of the clock game with unobservable actions created by BM, in which the game is played in real time (hence the term dynamic). For ease of explanation of the experiment later, we will frame the game environment as a stock market with a speculative bubble.

In this game, a finite number, I, of players participate in the stock market. At the start of the game, all players are in the market. They decide when to sell the stock. Each player can make exactly one selling decision before the game (or market) ends once they sell their stock, that is a final decision and they cannot buy it back.

The price of the stock starts at 1 and increases exponentially at the rate of g; that is, at the period of t, the price is e^{gt}. At any time period, sellers can *privately* sell their stock as long as the market is still open.

At one point in time t_0, a speculative bubble in the price starts. The random variable t_0 follows an exponential distribution[2] with parameter λ, whose probability distribution function is $f(t_0) = \lambda e^{-\lambda t_0}$. One interpretation of t_0 is that it is the period in which the current stock price starts exceeding the stock's true worth. The distribution of t_0 is a common knowledge, but the exact value of t_0 is unknown to sellers. Instead, seller i privately receives a signal at period t_i indicating that t_0 has happened (i.e., the price bubble has started). t_i is also a random variable which is uniformly distributed over the interval, $[t_0, t_0 + \eta]$. By the period $t_0 + \eta$, everybody has received the signal, so hence η is called the window of awareness. The signal arrival period is private information and sellers cannot observe others' signal arrival time.

Once K sellers have sold, the market crashes. If a seller successfully sells the stock before the market crash, he will receive the price of the stock at the time of selling; that is, if he sells the stock at period x, he will earn e^{gx}. His selling price is not observed by others. Once the market crashes, the rest of the sellers who did not sell on time only receive the post-crash price, e^{gt_0}, which is the price at the bubble starting period, t_0. Note that a seller can be worse off if he sells too early. Selling before t_0, say at t_x, means an opportunity loss since if he had waited, he could have earned e^{gt_0}, which is larger than e^{gt_x}.

There are two ways the market ends (crashes): (1) once $K(< I)$ sellers have sold, it crashes[3]; (2) it ends at the period of $t_0 + \tau^*$ if fewer than K sellers have sold the item by this period. τ^* is common knowledge and is assumed to be large enough to ensure players will not take this exogenous ending period into consideration of their selling strategy [7]. At the end of the market, the earnings of all sellers are publicly announced without individual identification.

This game structure has nice properties, which are conducive to experimental tests. First, the dynamic clock game has a unique symmetric Bayesian perfect equilibrium. Second, the equilibrium strategy is fully characterized by a fixed constant. More specifically, in the unique symmetric equilibrium, each player (assuming risk neutrality) employs the following simple strategy: wait for τ periods after signal arrival and then sell, where

$$\tau = \frac{1}{g} log(\frac{\lambda \Phi(K, I, \eta(\lambda - g))}{g - (g - \lambda)\Phi(K, I, \eta\lambda)})$$

and

$$\Phi(a, b, x) = \frac{(b-1)!}{(b-a-1)!(a-1)!} \int_0^1 e^{xz} z^{a-1} (1-z)^{b-a-1} dz.$$

Proof of the existence and uniqueness of the equilibrium is in BM [7].

The static version of the clock game is identical to the dynamic clock game except that agents precommit to a selling time after observing their private information. Thus, the static clock game is to the dynamic game as the first-price sealed bid auction is to ascending and descending price auctions. All the properties of the dynamic clock game except for the dynamic structure will carry over to the static clock game.

In the static clock game, all sellers are given their signal arrival time, t_i. Each seller is then asked to privately submit his selling time. Once all selling times are submitted, they are then compared and the market ending period is determined by the K-th earliest selling time. The K sellers with the earliest selling times can sell at their selling time. The $(I - K)$ sellers, whose selling times are later than the market ending period, did not sell in time, so they receive the post-crash price, e^{gt_0}. The variables, t_0 and t_i, are determined as in the dynamic game.

BM prove that the dynamic clock game is strategically equivalent to the static clock game: players in both types of the games should sell τ periods after their signals.

We test this theoretical equivalence between the dynamic and static clock games. This contrast is interesting because psychological forces could be different in the dynamic and static cases. For example, if subjects are anxious to resolve uncertainty in the dynamic game, and trade off this anxiety for expected profits, they will sell earlier in the dynamic game than in the equivalent static game (i.e. the delay after signal arrival will be shorter in the dynamic game).

3. Experimental Design and Methods

38 subjects were recruited from the UCLA CASSEL lab (19 males, 19 females; mean age = 20.9±4.1 year; age range = 17-

[2] An important property of the exponential distribution is that it is memoryless. Due to this memorylessness property, each period has a constant probability of λ of being t_0.

[3] If more than one seller sell exactly at the crash period, then a tie-breaking rule applies one of the tied sellers will be randomly (with an equal probability among them) chosen to sell his item.

42) and 25 subjects were recruited from Caltech (21 males, 4 females; mean age = 21.3$\pm$2.2 year; age range = 18-27).[4]

Before the experiment, subjects were informed about the experiment and gave informed consent to participate according to a protocol approved by Institutional Review Boards of the University of California, Los Angeles CA (for the UCLA sessions), and of the California Institute of Technology, Pasadena CA (for the Caltech sessions).

In addition to the \$5 show-up fee, subjects were paid whatever they earned during the experiment with the conversion rate of 100 Experimental Dollars equal to 0.50 US dollar.

Stimulus presentation and the timing of all stimuli and response events were achieved using Matlab (www.mathworks.com) and the Psychtoolbox (www.psychtoolbox.org) on computers running Microsoft Windows.

The experimental procedure followed the basic structure of the experiments by BM. The experiment was framed as an asset market in which subjects made selling time (price) decisions on the stock they were holding. Each participant played in his own market with computer players programmed to follow a theory-predicted equilibrium strategy. Participants knew that they were playing with five computer players (i.e., $I = 6$), who would receive the same amount of information as they did and who would employ a strategy constant throughout the experiment. The strategy of the computer players remained unknown to the participants.

An experimenter read instructions (see Appendix) aloud while participants were provided with copies of the instructions to read. To ensure that subjects understood the game structure and procedure, a quiz was administered at the end of the instructions. Subjects who failed the quiz (answered two or more questions incorrectly; see Appendix) twice were not allowed to proceed and dismissed ($n = 3$).

Each individual completed 100 trading rounds– 5 blocks of 10 dynamic clock game trials and 5 blocks of 10 static clock game trials. The dynamic blocks were interleaved with the static blocks and half of the subjects started with a block of dynamic trials and the other half with a static round block. In a dynamic trial, subjects were asked to make a real-time decision as to at what period (i.e., price) to sell the asset they were holding. At the start of each trading round, everyone (the subject and five computer players) received a share of the same asset with an initial price of \$1. This price grew exponentially at the rate of 4% in each period (i.e., $g = 4\%$) as trading time periods passed in real-time. Each period lasted 250 milliseconds. The computer screen displayed a trajectory of the price graphically as well as the current price numerically (Figure 1). The current price in each time period was the same for all 6 sellers (the human subject and 5 computer rivals).

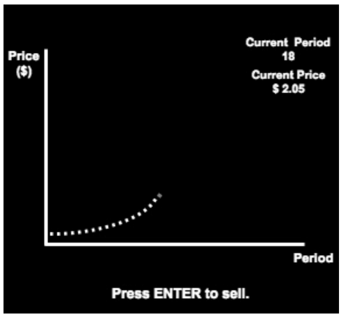

Figure 1: A dynamic clock game trial. The price trajectory from the start to the current period is displayed in a price-period graph. The current price and period are numerically displayed in the upper right corner of the screen.

At the start of each round, the computer determined the post-crash price, which was described, in instructions to the participants, as the maximum true value of the asset, or the value when the true value stopped growing (i.e., t_0). In each period, there was a 2.5% probability that the true value stopped growing (i.e., $\lambda = 2.5\%$). After the true value stopped growing, a subject received a message (or a signal) indicating that the current price of the asset is above its true value (Figure 2). This message is delayed by an amount of time that is equally likely to be anywhere from 0 to 60 periods (i.e., $\eta = 60$). Subjects were told that the delay between the time the true value stopped growing (t_0) and the signal arrival (t_i) was randomly chosen independently for each player in each round.

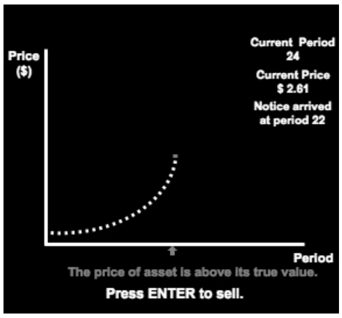

Figure 2: Subjects receive a message about the true value with a random delay.

Once three or more sellers in a market sold their asset, the round ended (i.e., $K = 3$). At this time, subjects received feedback about their current earnings as well as the prices at which other sellers sold their asset (Figure 3). A subject's earnings in a dynamic round were determined as follows: if the subject successfully sold the asset (i.e., he was among the first three sellers to sell), he received the price of the asset at the time of selling. Otherwise, the subject received an amount equal to the maximum true value of the asset (post-crash price).

In summary, the values of the parameters used in this experiment are as follows: Number of participants, $I = 6$; number of sellers necessary for market crash, $K = 3$; price growth

[4] Seven additional subjects participated in the experiment. They were excluded from the analysis either because their response time in many static trials was too short (these subjects either showed less than 2 seconds of average response time (RT) in static trials or responded less than a second for more than 30% of all static trials. The average RT across all other subjects was 6.66 seconds (SD = 2.91)) or their submitted selling times in static trials were highly correlated with initial, default values (explained further in the next section), implying that those subjects might have skipped trials by quickly pressing the response key instead of submitting their actual selling time decisions and thus added noise to the data. They obviously do not behave according to theory but also do not provide much insight about alternative theory, either.

Figure 3: Once the market ends, subjects receive information on their earnings and others selling price and the true value (the earnings of the last three subjects to sell).

rate, $g = 4\%$; the probability that the true value stops growing in each period, $\lambda = 2.5\%$; exogenous ending parameter, $\tau^* = 300$; window of awareness, $\eta = 60$.

With this set of parameter values, the equilibrium delay, τ, is 21 periods. That is, in equilibrium, once a subject receives a signal, he should strategically delay for 21 periods until he sells.

In a static trial, subjects were presented with all of the information that was revealed across time in the dynamic rounds, all at once. More specifically, the signal arrival time t_i was known to subject i at the beginning of a trial, who was then asked at what price (in what period) they would sell if they had received the signal in period t_i. The signal arrival period, t_i, varied between trials and was determined as in dynamic trials. The period in which a message arrived was shown on the computer screen. Subjects were allowed to explore the change in stock price over time by moving a cursor on the screen (Figure 4). Once the cursor was placed at the desired selling time, the participants would press the enter button to choose that time and proceed. Once they submitted their decision, the computer compared the selling times of all players (a human subject and 5 computer players) and determined earnings as in a dynamic round.

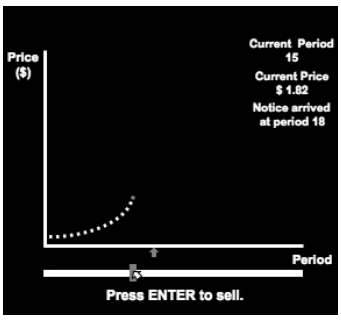

Figure 4: A static trading round. Subjects explore the price over time by moving the gray rectangular box along the horizontal bar at the bottom of the screen.

The initial position of the selling-time cursor is called an anchor and was randomized in every trial in order to avoid (or estimate) any potential anchoring effects.[5]

BM's original experiments used groups of six subjects. Our experiments used one subject in each six-person group with five computerized agents (who play the equilibrium strategy). Both all-human and one-human groups are of interest for different reasons.[6] First, we can control "collusive" strategies. Subjects cannot coordinate to wait longer than they would otherwise, and split the high payoff outside the lab. Second, participants do not face strategic uncertainty about behavior of other people; instead, they face the challenge of learning the computerized agents' strategy. Third, using computer opponents also prevents subject from being able to guess when other agents have sold from physical sound such as key pressing (i.e., information leakage).[7]

Our design permits within-subjects comparisons of the treatment effects of the two versions of the game, dynamic and static, which greatly enhances the power of the statistical tests. In a within-subject comparison each subject "acts as their own control"; this rules out the possibility that any measured differences in behavior in the two conditions are due to the idiosyncrasies of which group is solely assigned to which condition, as in between-subject designs [17].

Static trials test the strategic equivalence of static implementation and the dynamic version in BM. An additional benefit of static trials is that all selling decisions are observable. In dynamic trials, if the market ends before a seller would have sold, his strategic delay (the length of waiting periods between the signal arrival and the selling) is not observed and is therefore right-censored. In the dynamic structure we used, information about half of the subject-trials are censored in this way. In static trials, however, we learn the precommitted delay of all the subjects so no information is lost.

4. Results

We start with definitions of the terminology used in this section. Delay, an empirical measure of strategic delay τ, is the dependent variable of the most interest, and is defined as follows: In dynamic trials,

1. If a subject received the signal and then he sold the asset afterwards (before the market crash), *Delay* is **uncensored** (48% of the subject-trials[8]) and are defined as the number of periods between the signal arrival period and the selling time;

[5] In many decision making situations, an individual's final decision or behavior is influenced by an initial value or a reference point. This phenomenon is called anchoring [12]. The location of the initial position was recorded during the sessions at Caltech and these data were used as a check for subjects engagement in the task. Three participants at one of the Caltech sessions showed 40% to 60% correlation between their selling times and initial time anchor periods ($p < 0.005$) in static trials and hence were discarded for further analysis. Their average RT in static trials was also less than 2 seconds.

[6] Computerized agents have been used in many experimental studies on bargaining and auctions [13, 14, 15, 16].

[7] This was indeed a small challenge for BM since mouse-clicking noise could serve as an auditory cue about selling time to other subjects. To get around this issue, they had subjects hover the mouse over a button to sell, which unavoidably led to some erroneous sellings.

[8] This fraction, and all the others below, are very close for dynamic and static trials (see Table A1)

2. If the subject sold prior to or at the signal arrival period, *Delay* is **left-censored** (9%) and coded as zero (left-censored at 0);
3. If the subject received the signal but did not sell before the market crash, *Delay* is **right-censored** (26%) and coded as the number of periods between the signal arrival period and the market ending time;
4. If the subject neither received the signal nor sold (i.e., the market crashed before they got a signal) then *Delay* is treated as **missing** (16%) and typically discarded.

Although all selling decisions in static trials were indeed observed, for comparability of behavior in dynamic and static trials, *Delay* in static trials is defined in the same manner when we compare static and dynamic results.

Duration was defined as in BM, the length of periods from t_0 to the market ending. Early exit is an event in which a subject sold prior to the signal arrival and which led to left-censored *Delay*.

Success rate is the number of the trials in which a subject sold before the market ending, divided by the number of all trials.

Below we define the independent variables of relevance:

(a) *Signal* indicates the signal arrival time in periods;
(b) *Condition* is a categorical variable indicating a trial type (dynamic or static);
(c) *Group* is a categorical variable indicating the group to which a subject belongs (UCLA or Caltech);
(d) *UCLA (Caltech)* is a dummy variable for UCLA (Caltech): 1 if a subject participated in one of the UCLA (Caltech) sessions and 0 otherwise;
(e) *Dyn (Static)* is a dummy variable for dynamic (static) trials;
(f) *Experience* is a dummy variable to indicate a given trial belongs to the last half of the experiment.

In the following subsections, we first examine the trials where selling decisions were observed. Hence, therein *Delay* means left-censored or uncensored *Delay*. When the trials with right-censored *Delay* were included, the qualitative aspects of the data did not change and these additional results are reported in the appendix. Note that right-censored *Delay* is likely to underestimate actual *Delay*, and the left-censored *Delay* could overestimate the actual *Delay* that could have been negative, potentially biasing the results.[9] Therefore, we repeat all the analyses using static trials only, with a redefinition of *Delay* as the length of periods between the submitted selling time and the signal arrival time; $Delay_{uncensored}$ denotes this new definition of *Delay*. Note that $Delay_{uncensored}$ permits negative values when a subject sold prior to the signal arrival. Using $Delay_{uncensored}$ yields qualitatively identical to those obtained using the *Delay* measure.

In theory, all sellers are ex ante identical in a sense that in equilibrium they all employ the same unique symmetric strategy. Hence in analyzing data, we do not distinguish the behavior of 1st, 2nd, and 3rd sellers (following BM, who do the same). Reported *p-values* are two-sided unless noted otherwise.

4.1. Descriptive Statistics

First we describe some very basic properties of the data.

Due to sampling variation, the distribution of signal arrivals happened to be slightly different between the dynamic and static trials. As a result, the durations of trials are also slightly different (see Appendix). Later analyses control for these differences.

The success rates between dynamic ($M = 0.57, SD = 0.13$) and static trials ($M = 0.57, SD = 0.14$) were not significantly different in the two conditions or between subject pools.[10] However, it is noticeable that they are substantially above 50%, which is the fraction expected if subjects are playing the equilibrium delay strategy. (It is the first indication that they are generally selling earlier than the theory predicts.) The rates for dynamic and static trials are also highly correlated within subjects ($r(61) = 0.59, p < 4.24 \times 10^{-7}$; Appendix Figure A1), which indicates stable individual differences in how long subjects tend to wait in both conditions.

The next analyses look at properties of the distribution of delays after signal arrival, before selling. There are four basic results: Delays are shorter than predicted, longer in the static condition, depend on signal arrival time, and grow longer with experimental experience.

Short delays: Figures 5AB show the average of $Delay$ in the two conditions pooled, and within each subject pool. Using each individual's mean $Delay$ as a datum, the group averages are highly significantly below the theory prediction of $\tau = 21$.[11] The short average delays are substantially influenced by the left-censored observations (i.e., early pre-signal selling) which are set to zero. In static trials where all selling decisions are observed, the mean $Delay_{uncensored}$ is 19.23 ($Median = 16.76, SD = 10.35$), which is insignificantly different than $\tau = 21$ in a parametric test (one sample t-test, $t(62) = -1.36$, one sided $p = 0.18$), but is significantly different using a non-parametric test (one-sample signed-rank test, *z-value* $= -2.27, p = 0.02$).

Static delays are longer than dynamic delays: Figures 5AB compare delays in the static and dynamic conditions. A two-way ANOVA indicated both a significant difference between dynamic and static delay (the static delays are longer), and significantly shorter delays for the UCLA group (due to the difference in dynamic trials only). Figure 6 shows distributions of individual average $Delay$.

Delays depend on signal arrival time: In both the dynamic and static clock games, delays in selling after receiving a signal

[9] BM is aware of this censoring problem. To get around the problem, they estimated the delay measure using the Tobit procedure, assuming that the right-censored delay is normally distributed with mean τ. However, this specification is likely to yield an estimate in favor of τ.

[10] Paired t-test, $t(62) = -0.17, p = 0.87$; signed rank test, *z-value* $= -0.003, p = 0.997$). Between the UCLA and the Caltech subjects, dynamic trials: two-sample t-test, $t(61) = -0.64, p = 0.52$; static trials: two-sample t-test, $t(61) = -1.44, p = 0.15$.

[11] The tests are $t(62) = -5.32, p < 7.57 \times 10^{-7}$; signed rank test, *z-value* $= -4.40, p < 0.0001$). This pattern did not change when the trials with right-censored *Delay* were included (Figures A2, A3).

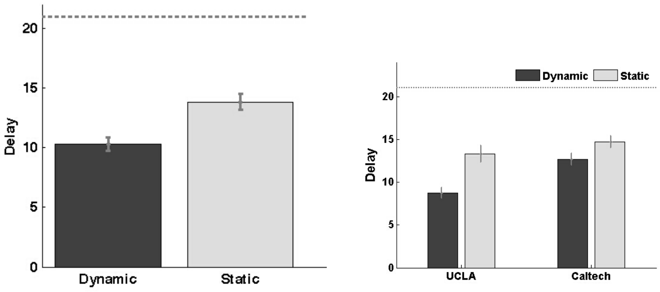

Figure 5: Difference in average *Delay* between dynamic and static trials. Dashed lines in red indicate the theory-predicted delay, $\tau = 21$. Error bars indicate standard errors. (A) *Delay* by trial type. (B) *Delay* by group and trial type.

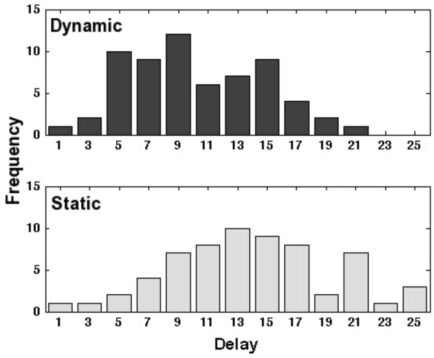

Figure 6: Distribution of individual average *Delay* between dynamic and static trials.

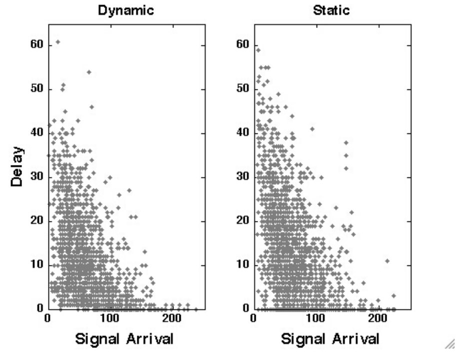

Figure 7: Distribution of *Delay* against the signal arrival period by trial type. Note that negative Delays are censored at 0.

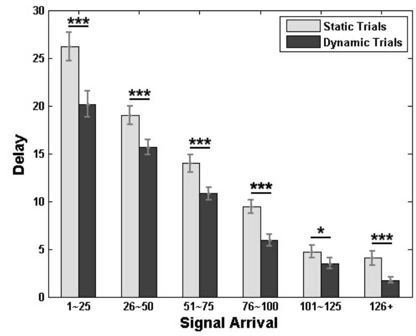

Figure 8: *Delay* as a function of the signal arrival period. *Delay* decreases as a signal arrives later. Error bars indicate standard errors. *** $p < 0.001, *p < 0.05$ (paired t-test, one sided).

should be constant, due to the "memoryless" property of the exponential distribution of underlying t_0. However, this property is quite counterintuitive; it means that conditional on not having received a signal, agents should behave in exactly the same way independently of the period they are in.

This predicted independence of delay from signal arrival is not evident in the data. Figure 7 shows scatter plots of *Delay* against the signal arrival time in dynamic and static trials. Delays are much longer for early signal arrival and much shorter for later signal arrival (left-censoring observations). We also binned the signal arrival periods into 6 bins, by 25 periods starting from 0, except for the last bin (rare signal periods over 125 periods were binned all together) and then compared *Delay* between dynamic and static trials in each of the 6 time bins. *Delay* decreased as a function of the signal arrival time in both dynamic and static trials. Further, in each time bin mean *Delay* in static trials was longer than in dynamic trials (Figure 8). This pattern was preserved when the trials with right-censored *Delay* were included (Figure A4).

We further examined if there is any group specific effect on *Delay* by conducting Tobit regression analysis [18] for *Delay* (Table 1). The effect of signal arrival time on delay is strongly significant across various model specifications. Both of the UCLA and the Caltech groups waited longer to sell in static trials than in dynamic trials, although on average the length of delay in static trials was longer in the Caltech group. Furthermore, the Caltech subjects exhibited less sensitivity of *Delay* to the signal arrival period in dynamic trials than in static trials. A similar pattern was found when the trials with right-censored *Delay* were included (Table A1). $Delay_{uncensored}$ also decreased as a function of the signal arrival period (Figure A5).[12] There is also tentative evidence that sensitivity of delay to arrival time was greater in subjects with higher risk-aversion.[13]

Experience and delay: Next we report whether subjects selling strategy was adaptive over time (see below for more detail). Comparing the first 50 and last 50 trials, the delays are longer in the last 50 trials and the dynamic vs. static difference in *Delay*

[12]Furthermore, $Delay_{uncensored}$ showed very different behavior between the two groups than shown by the previous analyses (Figure A6 and Table A3). The Caltech subjects showed less variance in *Delay* over all signal periods compared to the UCLA subjects. Caltech subjects' average length of $Delay_{uncensored}$ was shorter and the decrease in their $Delay_{uncensored}$ measure was less sensitive to the signal delay. In both subject groups, the signal arrival period was a highly significant predictor of $Delay_{uncensored}$, but the effect of the signal arrival period differed between the two groups: it was smaller (in an absolute sense) for the Caltech participants than for the UCLA participants.

[13]One clue about sensitivity of delay to arrival time comes from an analysis of risk preferences. In a subsample of 12 subjects we measured prospect-theoretic preferences over risky gambles using a procedure described elsewhere [19]. The sensitivity of delay to signal arrival (measured by a linear regression) was modestly correlated with utility function curvature over gains ($r(10) = 0.64, p = 0.025$) and losses ($r(10) = 0.48, p = 0.099$).

Table 1: Results of random-effects Tobit regression analyses for Delay censored at 0 (subject random-effects incorporated)

Variable	**A**	**B**	**C**	D	**E**	**F**
Constant	30.724†	29.15†	28.892†	28.612†	30.572†	29.418†
	(0.430)	(0.398	(0.472)	(0.486)	(0.430)	(0.672)
Signal	-0.196†	-0.194†	-0.194†	-0.190†	-0.204†	-0.202†
	(0.005)	(0.004)	(0.004)	(0.007)	(0.005)	(0.009)
*UCLA*Static*			3.231†		3.651†	4.537†
			(0.420)		(0.442)	(0.906)
*Caltech*Dyn*			0.521		-4.902†	-1.768*
			(0.573)		(0.799)	(0.996)
*Caltech*Static*			2.580†			1.461
			(0.576)			(0.971)
*Signal*UCLA*Static*				-0.009		-0.02
				(0.010)		(0.013)
*Signal*Caltech*Dyn*				0.010	0.038†	0.036**
				(0.007)	(0.011)	(0.013)
*Signal*Caltech*Static*				0.016		0.017
				(0.010)		(0.012)
Caltech	-0.250					
	(0.491)					
Static		2.787†		3.816†		
		-0.32		-0.651		
Log likelihood	-11527.7	-11498.8	-11488.4	-11491.7	-11491.2	-11477.7
Left-censored at *Delay* = 0		584				
Uncensored		3012				
Right-censored		0				
Included Observations		3596				

Standard errors are reported in parentheses. †$p < 0.0001$, ** $p < 0.01$.

is smaller in the last 50 trials (Figure 9). Regression analyses of $Delay_{uncensored}$ confirm these significant learning effects in both groups (Table A2).

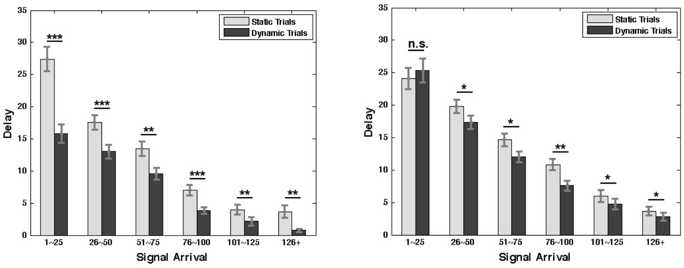

Figure 9: *Delay* as a function of the signal arrival period, moderated by experience. (A) First 50 trials. (B) Last 50 trials. *** $p < 0.001$, ** $p < 0.01$, * $p < 0.05$, n.s.: not significant (paired t-test, one sided)

We also measure learning at the individual level by defining $\delta = \sqrt{(delay - \tau)^2}$ which is the absolute deviation of delay choices from the predicted equilibrium τ and comparing δs in the first and second halves of 50 trials. Most of the subjects exhibited higher δ in the first half of the experiment than in the second half (Figure 10). Comparable results hold for $Delay_{uncensored}$ trials.

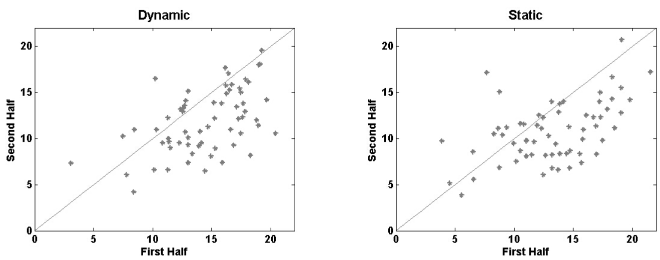

Figure 10: Scatter plot of average δs for the first and the last halves of the experiment. (A) Dynamic trials. (B) Static trials. Diagonal lines indicate 45 degree line. Significance tests: Dynamic trials, paired t-test, $t(62) = 6.14, p < 6.75 \times 10^{-8}$; signed rank test, *z-value* $= -5.09, p < 3.64 \times 10^{-7}$. Static trials, paired t-test, $t(62) = 5.78, p < 1.80 \times 10^{-6}$; signed rank test, *z-value* $= -4.60, p < 4.21 \times 10^{-6}$.

Although early exits before signal arrival should never occur in theory, there were early exits in 9.3% of all trials (584 incidents out of 6278). Early exits were more common for later signal arrival, for static trials, and in earlier trials compared to later trials (i.e., early exits were reduced by experience).

4.2. A comparison with the BM data

In this section, we report some new analyses of some of the original data from BM, for the purpose of comparison with our data.[14] The unobservable treatment in their paper has an identical structure to the dynamic trials in our experiment except for different parameter values and some procedural differences.

In the original BM experiments unobservable treatment, there were 6 experimental sessions and 12 human subjects participated in each session. In every trial, there were 2 independent groups; 6 subjects participated in one and the rest of them in the other. Each session consisted of 45 trials (called "rounds" by BM). Each experimental period lasted 500 msec in real time (ours were 250 msec). The following parameter values were used for the experiment:

(a) Number of participants: $I = 6$.
(b) Number of sellers necessary for market crash: $K = 3$.
(c) Price growth rate: $g = 2\%$
(d) The probability that the true value stops growing in each period: $\lambda = 1\%$
(e) Exogeneous ending parameter: $\tau^* = 200$
(f) Window of awareness: $\eta = 90$.

Under this parameter set, the (risk-neutral) equilibrium strategic delay τ is 23 periods, a little longer than the equilibrium $\tau = 21$ in our design.

Like BM, we discard the few observations in which selling occurs within the first 10 periods after the start of the trial. For comparability with our results, we did not distinguish sellers according to the order of their signal receiving time. All the definitions of the variables remain the same. Herein only trials with uncensored and left-censored *Delay*s (trials with successful selling) were analyzed.

In BM's data, mean *Delay* was shorter than the prediction, $\tau = 23$, in all sessions (Figure 11A). Most of the subjects exhibited mean *Delay* that is significantly shorter than 23 periods (one sample t-test, $t(71) = -18.81, p < 2.74 \times 10^{-29}$; signed rank test, *z-value* $= -7.33, p < 2.23 \times 10^{-13}$; Figure 11B).

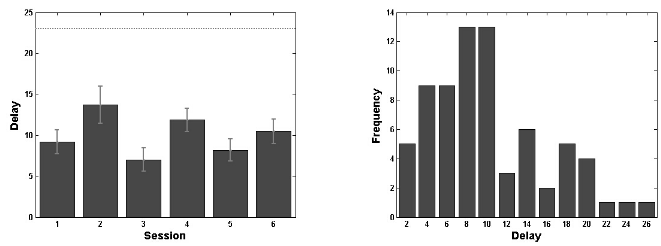

Figure 11: Average *Delay*. (A) *Delay* in different sessions. A dashed line indicates the theory-predicted delay, $\tau = 23$. Error bars indicate standard errors. (B) Histogram of *Delay*. Bin center: even numbers, starting at 2 and ending at 26; bin size: 2.

Delay was also dependent on the signal arrival time and was negatively correlated with the signal arrival time (Figure 12, Table 2). Note that the coefficient for the signal arrival time in the Tobit model (-0.209 in Table 2) is very close to those in our data (-0.190 – -0.204; see Table 1).

Further, we examined the effect of learning on *Delay*. Regardless of experience, the signal arrival time remained as a significant predictor of *Delay* (Figures 13, 14 and Table 3).

[14]Their paper also contains an interesting comparison of delays for the first three subjects to receive signals (which theory makes specific predictions about). They also contrast the unobserved-selling treatment with a treatment in which selling decisions are observed by all agents. In this "observed" condition all agents should sell immediately after the first sale is announced (due to a 'stampede' unravelling argument), which is essentially observed in the data.

Table 2: Results of random-effects Tobit regression analyses of *Delay* on the signal arrival time (subject random-effects incorporated)

Dependent Variable	*Delay*			
Independent Variable	Coefficients	Std. Err.	z-stat	p-value
Signal	-0.209	0.007	-29.11	0.0001
Constant	36.667	0.794	46.19	0.0001
Log likelihood	-4399.32			
Number of Groups	72			
Wald χ^2 test statistics = 847.16		p-value =	0.0001	
Left-censored Observations		452		
Uncensored Observations		1055		
Included Observations		1507		

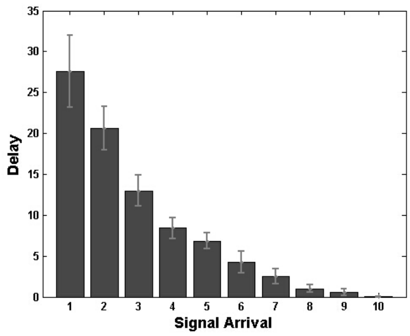

Figure 12: *Delay* as a function of the signal arrival period. Error bars indicate standard errors. X-axis: signal arrival period where **1** indicates signal arriving between 0 and 25; **2** between 26 and 50; **3** between 51 and 75; **4** between 76 and 100; **5** between 101 between 125; **6** between 126 and 150; **7** between 151 and 175; **8** between 176 and 200; **9** from 201 onwards.

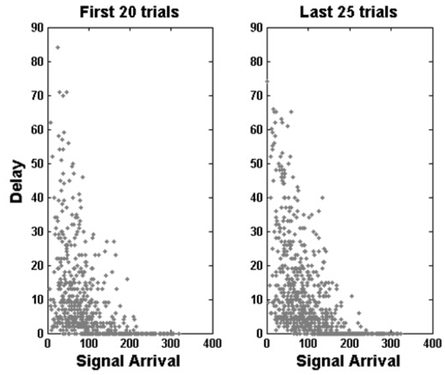

Figure 13: Scatter plot of *Delay* and the signal arrival time by experience.

However, *Delay* increased in the last 25 trials compared to the first 20 trials (Figure 14 and Table 3) as observed in our data (see $Delay$ in the dynamic trials in Figure 9).

The deviation measure δ increased as a function of the signal arrival time, but decreased in later trials (Table 4).

In summary, despite differences in design and procedures (e.g., human subjects competing against each other instead of computerized rivals; different parameter values), the BM data showed qualitative results similar to ours.

5. Learning and anxiety

Previous literature has not considered how a player's delay changes through learning across trials. In this section we propose a specific model and simulate its behavior to see how well the simulated patterns fit statistical features of the data.

Some strategic learning models in literature are possible candidates (see Camerer [20]). Reinforcement learning models adjust the numerical strength of a strategy based on its past successes and failures (and numerical strength is mapped into choice probability in some way). In the clock game setting, a strategy corresponds to a particular selling time as a function of signal arrival. The shortcoming of these types of models in games like this, with many strategies and relatively few strategies, is that reinforcement does not learn fast enough to match the empirical pace of human learning observed in experimental data.[15] For reinforcement learning to work, each possible strategy has to be sampled several times. In this game, there are 300 choices of times when a player can sell, and only 100 trials, so simple reinforcement is likely to learn too slowly without modification.

Another popular model is "fictitious play", in which players build up statistical belief about the likely choices of opponents. The limit of this model is that in the experiments, subjects only learn about bounds on the previous choices of two or three opponents (out of five), since all they find out for certainty is when the market ended. So without more assumptions about beliefs from partially-observed data the model cannot be applied.

An alternative is reinforcement plus "fictive learning" (e.g., a key element of EWA [23]). Fictive learning simply refers to adjustment of strategy likelihoods from model-based knowledge of the payoffs that would have been earned from a strategy

[15]This limit of reinforcement learning has been known for many years. It produces especially poor results in many-person games in which only one person earns a reward (e.g., "market games" [21]; LUPI lottery games [22]; and auctions). Two interesting generalizations which sometimes fit actual learning better are the inclusion of an aspiration level, and/or spreading reinforcement from one strategy to neighboring strategies. Both of these modifications are practically similar to including fictive learning as in EWA and other models.

Table 3: Results of random-effects Tobit regression analyses of *Delay* on the signal arrival time and experience (subject random-effects incorporated)

Independent Variable	A	B
Constant	34.973†	34.342†
	(0.872)	(1.118)
Signal	-0.211†	-.202†
	(0.007)	(0.011)
Experience	2.907†	4.143*
	(0.697)	(1.432)
*Signal * Experience*		-0.0139
		(0.014)
Log likelihood	-4388.37	-4388.93
Number of Groups	72	72
Wald χ^2 stat. (p-value)	867.93 (< 0.001)	870.51 (< 0.001)
Left-censored Observations	452	452
Uncensored Observations	1055	1055
Included Observations	1507	1507

Standard errors are reported in parentheses. $\dagger p < 0.0001$, $*p < 0.005$.

Table 4: Results of random-effects regression analyses of δ on the signal arrival period and the trial number (subject random-effects incorporated)

Dependent Variable	δ			
Variable	Coefficients	Std. Err.	z-stat	p-value
Signal	0.038	0.002	15.82	0.0001
Trial #	-0.023	0.006	-3.53	0.0001
Constant	14.235	0.514	27.71	0.0001
R^2	0.1427			
Number of Groups	72			
Wald χ^2 test statistics = 260.86	p-value =	0.0001		
Included Observations	1507			

The interaction between Signal and Trial # was not significant and thus not included.

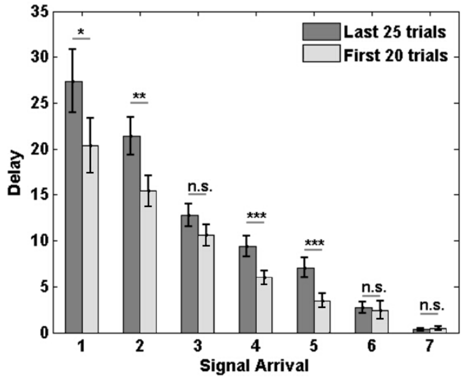

Figure 14: *Delay* as a function of the signal arrival period, moderated by experience. *** $p < 0.01$, ** $p < 0.02$, * $p < 0.07$, n.s.: not significant (paired t-test, one-sided). X-axis: signal arrival period where **1** indicates signal arriving between 0 and 30; **2** between 31 and 60; **3** between 61 and 90; **4** between 91 and 120; **5** between 121 and 150; **6** between 151 and 180; **7** from 181 onwards.

that was not chosen (also called its foregone payoff). Fictive learning is faster because it allows adjustment of strategies that were considered but not played. There is also accumulating evidence that fictive learning prediction error signals are present in the dopaminergic system [24] and in monkey neural firing rates [25].

To simplify the analysis, and fit the feedback properties of the experimental data, we exploit the fact that a player's payoff is only affected by the selling time of the *third* player, which is dependent on the signal arrival time. Given this, we propose the following learning rule across trials in the clock game:

- Denote periods by n, and the estimate of the third seller's delay after period n by $\hat{\tau_3}(n)$. Initialize $\hat{\tau_3}(0) = 0$. This initialization is chosen to see how well the model can learn that sellers delay substantially after signal arrival, from a starting point of no delay at all.

- Infer the fundamental period, t_0, and the third seller's selling time, t_3^{sell} from the payoff feedback at the end of the period. (Keep in mind that at the end of each period, subjects learn the payoffs to all players. The payoffs to the three players who did not sell before the market crash reveal $t_0(n)$). Obtain an estimate of $\tau_3(n)$ after period n from feedback using:

$$\hat{\tau_3}^* = t_3^{sell}(n) - E[t_3^{signal}(n)|t_0(n)] \qquad (1)$$

  Here the expected signal arrival time for the third seller given the fundamental signal time, $E[t_3^{signal}(n)|t_0(n)]$, is $t_0(n) + h(\eta)$, since the signal arrives after t_0 within a time window of length η. The quantity $h(\eta)$ is the expected value of signal arrival time for the third-fastest signal (the third-order statistic of the six draws for signal arrival), which is $h(\eta) = \frac{3}{7}\eta$. [16]

- Given the estimate of $\hat{\tau_3}^*$, update $\hat{\tau_3}(n)$ according to the learning rule:

$$\hat{\tau_3}(n) = \hat{\tau_3}(n-1) + \alpha(\hat{\tau_3^*} - \hat{\tau_3}(n-1)) \qquad (2)$$

  where α is a learning rate. A higher value of α represents faster learning. Note that for simplification, if learning player i is the player who sells third, then the same updating equation holds using her own observed delay in place of $\hat{\tau_3^*}$

The model assumes that during a trial, players are constantly adjusting beliefs about signal arrival, forecasting when the third seller is likely to sell, and maximizing their expected payoffs given those beliefs. Each player maintains an adjustable belief that the current time, t, is before the likely selling time t_3^{sell}, $P(t < t_3^{sell})$. The expected value of selling at time t is given by

$$EV(t) = e^{gt}P(t < t_3^{sell}) + E[e^{gt_0}]P(t > t_3^{sell}) \qquad (3)$$

where $E[e^{gt_0}]$ is the expected end-of-game payoff. For simplicity, we assume that the player maintains a point estimate of the third player's selling time, $t_3\hat{(n)}$. Thus $P(t < t_3^{sell})$ is a step function, with $P(t < t_3^{sell}) = 1$ if $t < t_3(n)$ and 0 otherwise.

To estimate t_3^{sell} we assume that the player uses the estimated strategic delay of $\hat{\tau_3}(n)$ after receiving her signal at t_3^{signal}. Then the estimate of the 3rd player's selling time is

$$t_3^{sell} = \hat{\tau_3}(n) + E[t_3^{signal}|t_i^{signal}] \qquad (4)$$

where $E[t_3^{signal}|t_i^{signal}]$ is the expectation of the 3rd player's signal arrival time, given that her own signal arrived at t_i^{signal}. Given eq. 3 and eq. 4, the player will sell at time $t_i^{sell} = \hat{t_3}(n)^{sell} - 1$. Selling decisions are different in the static and dynamic case.

- Static case: The player knows her own signal arrival time t_i^{signal}. Since she has no idea whether her signal arrival was early or late (compared to other players), the expected signal arrival time of the third seller is given by:

$$\begin{aligned} E[t_3^{signal}|t_i^{signal}] &= \int_{t_i^{signal}-\eta}^{t_i^{signal}} \phi(t_0|t_i^{signal})E[t_3^{signal}|t_0] \\ &= \int_{t_i^{signal}-\eta}^{t_i^{signal}} \phi(t_0|t_i^{signal})(t_0 + h(\eta)) \\ &= E[t_0|t_i^{signal}] + h(\eta) \end{aligned}$$

  where the conditional probability of the fundamental time t_0 given player i's signal arrival time t_i^{signal}, $\phi(t_0|t_i^{signal})$ is given by:

$$\phi(t_0|t_i^{signal}) = \frac{\lambda e^{-\lambda t_0}}{1 - e^{-\lambda t_i} - (1 - e^{-\lambda(t_i - \eta)})} \qquad (5)$$

- Dynamic case: There are two cases to consider–when the signal has or has not arrived by the time of the selling decision. If the signal has arrived, the expectation and selling decision strategy is the same as in the static case.

[16] The distribution of the k-th order statistic out of I items for uniformly distributed values between $[0, \eta]$ is Beta distributed, $U_{(k)} \sim Beta(k, I + 1 - k)$, with an expected value of $E[U_{(k)}] = \frac{k}{I+1}\eta$. This is equal to $\frac{3}{7}\eta$ in our case, with $I = 6$ and $k = 3$.

If the signal has not arrived at time t (i.e., $t < t_i^{signal}$), the player estimates:

$$E[t_0] = \frac{1}{\lambda}$$
$$E[t_3^{signal}|t_i^{signal}] = \frac{1}{\lambda} + h(\eta)$$

Based on the above, we can construct a simple algorithm for decision-making in the clock game if players follow this learning rule:

- Static condition: In period n, the player i sells at time t_i^{sell}, given by:

$$t_i^{sell}(n) = \hat{\tau_3(n)} + E[t_0|t_i^{signal}] + h(\eta) - 1 \quad (6)$$

- Dynamic condition: The player waits until period $\frac{1}{\lambda} + h(\eta)$ for the signal. If it does not arrive by then, the player sells. If the signal arrives by then, the player sells at the same period $t_i^{sell}(n)$ as in the static case.

- Learning: Learning is expressed entirely by the linear updating of the estimate $\hat{\tau}(n)$ based on the feedback from the end of the trial, using the fictive learning rule given in the previous section.

The decision rule given above does not predict one key empirical aspect of behavior: the negative correlation between delay and signal arrival time. There are two likely explanations for this relation. One is that subjects misperceive the memoryless property of the exponential distribution of window-of-awareness initiation; so they think if they got a signal early in the trial their signal was probably relatively early, and if they got a late signal their signal was probably relatively late. The other possible explanation is that there is nonpecuniary emotional penalty for waiting to sell, due to anxiety which grows throughout the trial. We explore the latter possibility by simply including a reduced-form anxiety term χt which speeds up the selling decision.

$$t_i^{sell}(n) = \hat{\tau_3(n)} + E[t_0|t_i^{signal}] + h(\eta) - \chi t \quad (7)$$

The anxiety term grows linearly with time and the player has a stronger tendency to sell earlier as time increases.

We can now summarize the predictions of the decision rules decribed above:

- Delay decreases as signal arrival time increases:
  This is due to the linearly growing anxiety term χt. Players sell at a comparatively earlier time, and the delay-signal arrival relation is more negative, if the anxiety parameter χ is higher.

- Players can sell before receiving a signal, and there are more of these early sales in the dynamic condition:
  If the signal arrives very late, the players will sell earlier than their signal arrival time. In the dynamic condition, the players will sell at period $\frac{1}{\lambda} + h(\eta)$ if the signal doesn't arrive by then. So there will be a greater number of early sales in the dynamic condition.

- Delay increases with learning:
  If the initial estimate of the canonical delay $\hat{\tau}$ is low, then players' beliefs converge towards the equilibrium delay τ with learning, according to the fictive learning rule. Their own selling delays will also increase with learning.

5.1. Behavioral delay responses to regret

This fictive learning model posits that the change in the player's delay in the next round will be influenced by the estimation error $\hat{\tau_3}^* - \hat{\tau_3}(n)$ times the learning rate α. We can see evidence of this relationship in the behavioral data. Define a player's regret as the difference between the player's selling time and the selling time of the third seller. In figure 15, the player's regret is plotted on the x-axis. If the player does not sell in time she incurs negative regret; if she sells too early regret is positive regret. On the y-axis, we plot the change in that player's delay in the following round. A linear fit to the data gives a slope of 0.32. Thus, for every period of positive regret (early selling), the delay in the following round goes up by 0.32 periods.

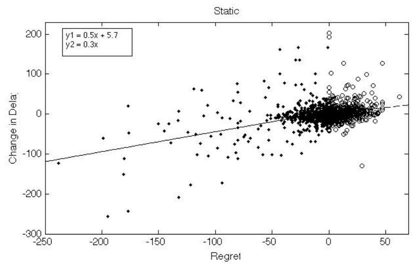

Figure 15: The change in delay in the following round when the player sells too early or too late and incurs regret in the static condition. Slope of linear fit is 0.5 when player sells too early, and 0.3 when he sells too late.

In the dynamic condition, the game ends when the third player sells. Therefore, there is only a bounded measure of when three of the players, who "virtually" sold too late, would have sold. However, there is a measure of early (negative) regret when a player sold too early. We plot the player's regret versus change in delay for the dynamic case in figure 16. That slope is .69 periods. This seems to be substantially higher than adjustment in the static case, but there is no clear way to compare the two adjustment slopes.

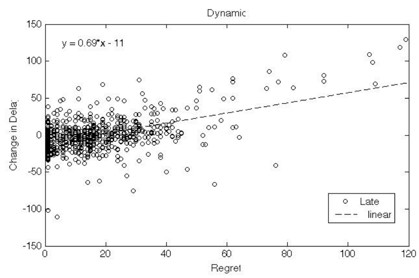

Figure 16: The change in delay in the following round when the player sells too early and incurs positive regret in the dynamic case. Slope of linear fit: 0.69.

5.2. Simulations

We run simulations of the model to investigate the effects of the learning rate, α, and anxiety, χ, parameters. We varied the parameters α between 0 and 0.2 in increments of 0.02, and χ between 0 and 0.2 in increments of 0.1. We ran 50 simulations for each pair of parameter values using different seeds. We note the following results:

- There is a negative correlation between delay and signal arrival time for both the static condition, shown in Figure 17, and the dynamic condition, Figure 18. We plot the resulting delay for different values of χ.
- The delay increases for faster learning rate α, as shown in Figure 19 for the static case for trials 26-50, and in Figure 20, for the dynamic case.
- The simulated player's estimate of the canonical delay of the third sell, $\hat{\tau_3}$ converges towards the equilibrium delay after learning in both the static (Figure 21) and the dynamic conditions.
- The delay increases significantly after learning, as shown in Figure 22 (trials 1-25) and Figure 23 (trials 26-50). The number of early exits also significantly lessens in the later trials for both the static and dynamic conditions. However, the delay is generally shorter, and the number of early sales greater, in the dynamic compared to the static condition.

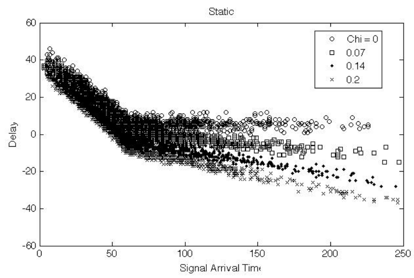

Figure 17: Delay in the static case as a function of the signal arrival time (in trials 26-50 of learning). Different delays are observed when the anxiety parameter is varied from 0, 0.07, 0.14 to 0.2.

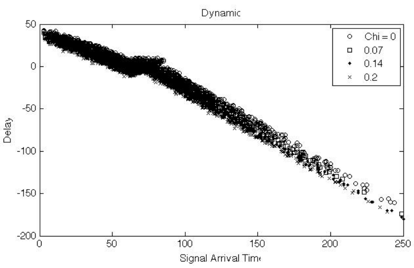

Figure 18: Delay in the dynamic case as a function of the signal arrival time (in trials 26-50 of learning). Different delays are observed when the anxiety parameter is varied from 0, 0.07, 0.14 to 0.2.

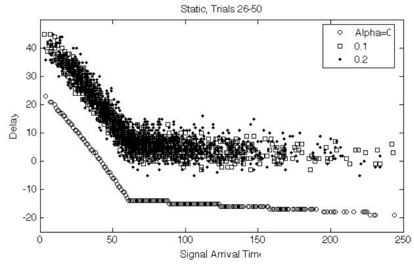

Figure 19: Effects of delay in the static case after learning: 26-50 trials. The learning rate is varied from 0 to 0.1 to 0.2.

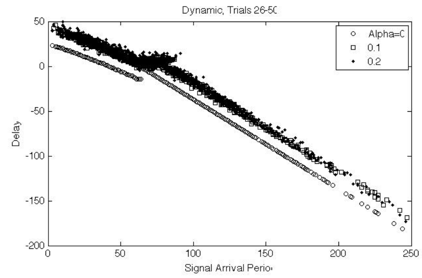

Figure 20: Effects of delay in the dynamic case after learning: 26-50 trials. The learning rate is varied from 0 to 0.1 to 0.2.

5.3. Parameter fits from behavioral data

We find the values of the parameters α and χ that match the behavioral data as closely as possible. For this purpose, we need to find an appropriate metric to compare actual data and simulated data. We use the absolute deviation from the equilibrium delay, $\delta_i = \sqrt{(delay_i - \tau)^2}$. This is a good metric if the goal is to explain when the behavior deviates from equilibrium. We consider values of α between 0 and 0.2 in gradations of 0.02, and χ between 0 and 0.2 in gradations of 0.1.

For each pair of parameter values, we compute the mean absolute difference between the deviation from the equilibrium delay from the simulation at period t, $\delta_i(\alpha, \chi)(t)$, and the deviation for the actual player, across all the 50 periods, for each player Thus,

$$Err(\alpha, \chi) = \frac{1}{50} \sum_{t=1}^{50} \sqrt{(\delta_i(\alpha, \chi)(t) - \delta_i(t))^2} \tag{8}$$

We find the pair of value $\hat{\alpha}$ and $\hat{\chi}$ for which the error, $Err(\alpha, \chi)$, is minimized. Table 5.3 shows the best fits for all the subjects combined in the Caltech and UCLA pools. In the Appendix, Tables A4 and A5 show the best fit for individual subjects in the Caltech and UCLA pools.

Pool	Mean Dev	Std Error	Anxiety	Learning Rate
Caltech	10.49	2.04	0.03	0.16
UCLA	12.77	1.96	0.04	0.11

Table 5: Best fit to the aggregate behavioural data for the Caltech and UCLA subject pools.

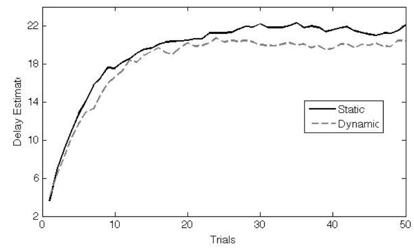

Figure 21: The estimates of τ_3 after learning, against the number of trials, for the static and dynamic conditions. The initial estimate at time t=1 is 0. The learning rate, $\alpha = 0.2$.

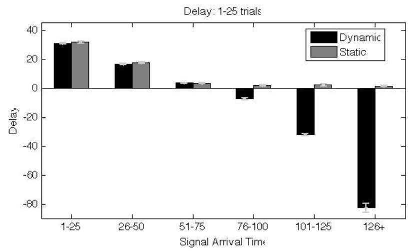

Figure 22: Effects of delay in the static and dynamic case during learning: 1-25 trials. The delay in the dynamic case is significantly less than in the static case.

6. Discussion and Conclusions

The clock games we explore experimentally are models of situations in which investors receive a signal that an asset value has stopped growing (its fundamental value has been determined), but also know that others may not have received the signal yet. Therefore, in equilibrium there is a period of delay in which all investors can know the price is above the fundamental, but keep trading anyway but it is not commonly known that prices are too high. BM define a general class of "clock games" with nice structure that makes many sharp predictions. The central feature of the games is how long people wait to sell after finding out (with certainty) that the asset is overpriced; this waiting period is called the "delay".

Our paper replicates and extends findings in the original experimental paper of BM [7, 8]. An important contribution is that we replicate a basic finding of their paper, which is that actual delay is reasonably close to the delay predicted in equilibrium (assuming risk-neutrality), and with learning over repeated trials actual delays move in the direction of equilibrium. However, we also focus on three major empirical findings that are not explained by the existing theory, and show how extended theories can explain these interesting deviations.

First, the subjects' strategic delay decreased as a function of the signal arrival period, despite the theoretical prediction of a fixed delay, independent of the signal arrival time. The fact that delays were lower when signals arrived later holds for all subject pools, experimental conditions (static and dynamic), persists throughout the experiment, and is true when human subjects competed against other human participants (in BM data) and when they faced computerized opponents choosing equilibrium delays (in our data). The signal dependence could be due to misperception of the memoryless process underlying the as-

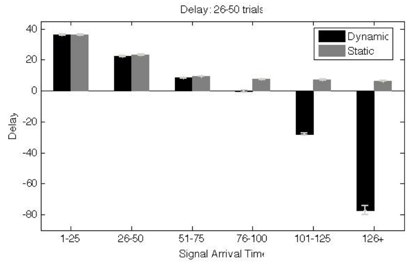

Figure 23: Effects of delay in the static and dynamic case after learning: 26-50 trials. The delay in the dynamic case is significantly less than in the static case, however the delay has increased significantly after learning for both conditions.

set values, but we also show in simulations that it is consistent with a growing sense of anxiety, a preference for trading off anxiety with money. (We'll say more about anxiety shortly).

Second, we found that the subjects' strategy changed as they gained more experience (this was also noted by BM but not explored in their paper). Across trials, delays grew longer and the negative relation between signal arrival and delay became smaller. We show in some simulations that a model of fictive learning about the selling time of the third-selling player, could reproduce some of these learning effects.

Third, and most interestingly, we compared a dynamic version of the game (played over time) and a static version in which signal arrival times and selling delays are all committed in advance, then combined to determine an outcome (like sealed bid auctions). The subjects consistently sold more rapidly (i.e., had shorter delays) in the dynamic clock game than in the static game.

One explanation for the static-dynamic behavior difference is that given time constraints, reasoning and strategic computations in dynamic trials were not as precise as in static trials and led to more erroneous decisions. However, if this explanation was correct, errors should be diminished as the subject gain more experience. Indeed, in later trials the dynamic and static differences were attenuated, but did not disappear and remained significant in later trials. (Also, exactly the opposite argument is sometimes made to account for the fact that bidding in sealed-bid auction is often different than in structurally equivalent ascending price auctions; e.g., Kagel and Levin [26]). Another possibility is that subjects were trying to speed up the experiment to increase hourly earnings, but this is unlikely for several reasons.[17]

A more likely explanation is that simply waiting for the

[17] If the subjects had wanted to finish the experiment earlier to do something else or just for leisure, every second they waited could have incurred an implicit constant opportunity cost or a shadow price of waiting. However, because they were competing with the computer rivals, they could not actually speed up the experiment as they would have wished. Had they sold early in order to terminate the round, they would have still had to wait until the other two computer players sold, not earning as much. In addition, note that the average delay signal for each time bin in the dynamic case actually increased, rather than decreasing in later trials. This seems inconsistent with the shadow price argument since by then, distracted subjects most likely would have been even more bored of playing the same game over 50 times (which means increased shadow price). Also, they could have actually sped up the static trials by keeping on pressing the enter key and submitting the randomly selected anchor values in every static

trial to progress generates more anxiety in the dynamic case. In the dynamic trials, a subject makes a flow of decisions between selling now or waiting another period in every period, in a faced-paced environment, under time pressure–each period only lasts a quarter of a second. Participating in a rapidly progressing, dynamic game can be stressful, anxiety provoking, and reduce perceived control[18]. The decision to wait means another decision in the next period, and this might have come at a psychological cost such as stress or anxiety, resulting in the shorter delay in dynamic trials.[19]

Anxious subjects could reasonably trade off profit from waiting longer for a reduction in anxiety by selling sooner than predicted by a no-anxiety benchmark. This hypothesis is also consistent with a substantial literature on preference for resolution of uncertainty in other areas of economics [29, 30, 31, 32, 33, 34].

Of course, to explain the fact that delays do get longer with experience in the dynamic condition requires a further assumption that anxiety is reduced across the experiment as subjects get acclimated, which is plausible but not directly observed.

The conjecture that early selling is due to anxiety could be tested in further experiments. For example, if the anxiety hypothesis is correct, then increasing the clock time per period should create earlier selling (assuming anxiety is a function of clock time rather than just the number of periods). Another interesting treatment would be to exogenously decrease or increase stress and anxiety levels, and see if selling delays shrink. (For example, Porcelli and Delgado[35] induce stress using a cold-pressor task in which subjects immerse their hands in icy water for two minutes, and show that risk aversion expressed by gamble choices increases due to stress). Inducing anxiety in the dynamic case only would further reduce the delay, and anxiety in the static case only would decrease the gap between the two conditions. If empirically proven, a model incorporating risk aversion and distaste for anxiety built in the utility function could provide a more accurate description of timing decision making.

round. However, most of the subjects indeed took time to explore and submit their own selling times, and this was evidenced by the fact that their selling times were uncorrelated with the default anchor values. On a side note, this kind of waiting game could be quite engaging. In Cox et al.[17], they compared the Dutch auction with the first-price sealed bid auction using lab experiments to test the strategic equivalence between the two mechanisms. They found that the prices in the Dutch auction were lower than those in the first-price auction. One of their explanations of this discrepancy was that subjects got additional utility, the utility-of-suspense from playing the Dutch auction waiting game, and hence they waited longer, decreasing the prices. This was based on many subjects comments that they enjoyed the Dutch auction experiment more than the other auction formats because of the suspense of waiting. In personal conversations, some of the subjects in this study also made similar comments.

[18] Jap [27], in field interviews with suppliers participating in reverse auctions, found that the compressed time frame of open-bid auctions creates a stressful context for the supplier and many suppliers complained that the format prevented them from carefully considering price bids and gave them a sense of being out of control.

[19] Wood and Schweitzer[28] in their experiments induced different levels of anxiety (high vs. low) and found negotiators experiencing high levels of anxiety make steeper concessions and exit bargaining situations earlier.

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Appendix

Additional Results

Table A1: Percentage of trials with (un)censored $Delay$

	All	Dynamic	Static
Right censored	26%	25%	28%
Uncensored	48%	49%	47%
Left censored	9%	8%	10%
Missing	16%	18%	15%
Total	100%	100%	100%

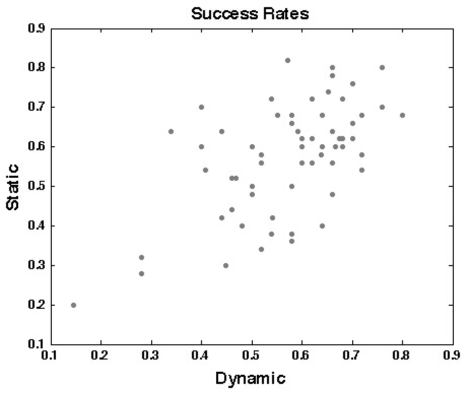

Figure A1: Scatter plot of success rates in dynamic and static trials.

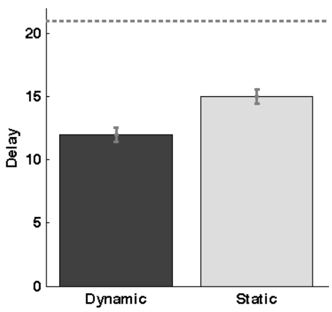

Figure A2: Distribution of individual average *Delay* between dynamic and static trials. The trials with right-/left-censored or uncensored *Delay*s were included.

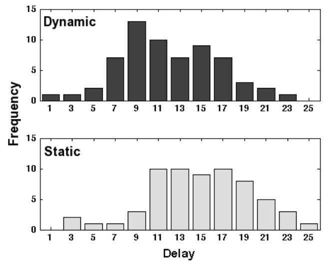

Figure A3: Difference in average *Delay* between dynamic and static trials. The trials with right-/left-censored or uncensored *Delay*s were included. A dashed line indicates a theory-predicted delay, $\tau = 21$. Error bars indicate standard errors. Paired t-test, $t(62) = -5.46, p < 8.93 \times 10^{-7}$; signed rank test, *z-value* $= -4.57, p < 0.0001$.

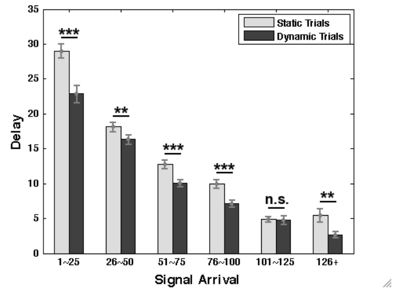

Figure A4: Delay as a function of signal arrival period. Delay decreases as a signal arrives late. The trials with right-/left-censored or uncensored *Delay*s were included. Error bars indicate standard errors. $***p < 0.001, **p < 0.01$, n.s.: not significant (paired t-test, one sided).

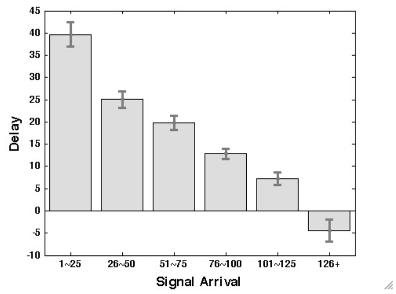

Figure A5: $Delay_{uncensored}$ as a function of the signal arrival period.

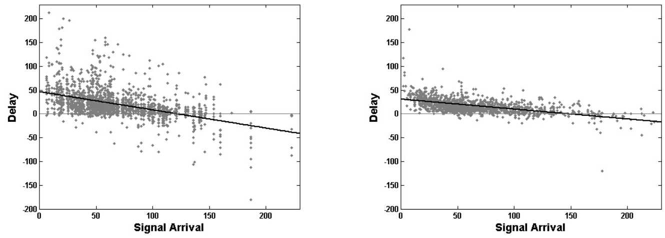

Figure A6: Scatter plot of $Delay_{uncensored}$ versus the signal arrival period. Straight lines indicate fitted regression lines from B in Table A3. (A) UCLA subjects. (B) Caltech subjects.

Table A2: Results of regression analyses of $Delay_{uncensored}$ on the signal arrival time and experience

	UCLA subjects only			Caltech subjects only		
Variable	A	B	C	D	E	F
Constant	46.502†	46.103†	50.864†	29.858†	31.004†	31.270†
	(1.454)	(1.276)	(1.764)	(0.760)	(0.701)	(1.000)
Signal	-0.382†	-0.392†	-0.444†	-0.211†	-0.230†	-0.233†
	(0.017	(0.017)	(0.022)	(0.009)	(0.011)	(0.014)
Experience	-0.226		-9.897†	2.073**		-0.521
	(1.218)		(2.544)	(0.730)		(1.402)
Signal*Experience		0.030⋄	0.146†		0.033†	0.039*
		(0.016)	(0.034)		(0.009)	(0.018)
R^2	0.2168	0.2183	0.2245	0.3077	0.3102	0.3103
Adjusted R^2	0.216	0.2174	0.2232	0.3066	0.3091	0.3086
F-statistic	262.58	264.84	182.92	277.13	280.42	186.86
Prob(F-statistic)	<0.001	<0.001	<0.001	<0.001	<0.001	<0.001
Included Observations	1900	1900	1900	1250	1250	1250

Standard errors are reported in parentheses. $\dagger p < 0.0001$, $** p < 0.01$, $*p < 0.05$, $\diamond p < 0.1$

Table A3: Results of random-effects regression analyses of $Delay_{uncensored}$ (subject random-effects incorporated)

Variable	A	B
Constant	40.813†	45.875†
	(1.726)	(1.787)
Signal	-0.299†	-0.374†
	(0.010)	(0.013)
Caltech	-4.019	-15.280†
	(2.547)	(2.798)
*Signal * Caltech*		0.168†
		(0.019)
R^2	0.217	0.234
Included Observations		3150

Standard errors are reported in parentheses. $\dagger p < 0.0001$.

Instructions

Thank you for participating in this experiment on the economics of investment decision making. By participating, you have already earned a $5 show-up fee. If you follow the instructions carefully you may be able to make additional money that will be paid to you at the end of the experiment privately, in cash. The dollar amounts mentioned below (and on your screens) are experimental dollars. We will use a fixed conversion rate to convert experimental dollars to real cash. The conversion rate is 100 Experimental Dollars = 0.50 US Dollar

You are about to make selling decisions 100 times in a row. Each round represents one trading round. You will be paired with 5 other **computer** players, who are also sellers, in every round. Note that you are **NOT** playing with other human participants in the room. To make sure you understand the procedure, please complete the quiz following these instructions. If you cannot answer the quiz questions yourself (with a little guidance from us) you will not be allowed to proceed. Please see the power point slides in front of you for the figures referred to below.

Half of the rounds will be played in a dynamic condition and the other half in a static condition. We will explain these two conditions next.

Dynamic Trading Rounds In a dynamic trading round, your job is to decide in real time when to sell an asset you are holding. At the start of each trading round, everyone gets one share of the same asset. The price of the asset begins at $1 (figure 1) and grows exponentially as trading time periods pass (figure 2).

Each period lasts 250 milliseconds. In every period you are making a real-time decision about whether to sell or whether to wait. When you decide to sell your asset, press the ENTER key. Once you have decided to sell, you have no more decisions to makeyou just wait until the trading round ends. That is, you make one and only one selling decision in each round.

The price of the asset increases by 4% in each trading period. You will see the price increasing on your computer screengraphically in the price-period plot at the center of the screen. The *graph* of prices is shown in the center of the screen (figure 3) and the *numerical* price is shown in the top right corner (figure 4). The current price is the same for all sellers (you and five *computer* players).

It is possible that the price graph will go out of the top of the screen in a very long round (figure 5). This is normal and does not change anything about your decisions. Even if the graph hits the top of the screen, the current price will continue to rise and is displayed on the top right of the screen.

There are two ways a trading round can end:
(1) Once 3 players have all decided to sell; or
(2) The trading round reaches 300 periods after the **true value** (explained below) of the asset has stopped growing, even though fewer than three players have sold.

These rules mean that among the 6 players (including you and five other computer players), **only** 3 players can actually sell their stock before the round ends. If you sell before the round ends, you earn an amount in $ equal to the price at which you sold. If three others sell before you do, and the round ends, then you will earn the maximum **true value** of the asset, as explained below.

Here is how the **true value** is determined. At the start of each trading round, the computer randomly selects a trading period at which the true value growth will stop. The true value is equal to the asset price until this pre-determined stopping period; that is, the true value grows with the price (at the rate of 4%) and stops growing after the pre-determined stopping period is reached, while the price continues to grow (at the rate of 4%) in excess of the true value. The <u>maximum true value</u> of the asset is equal to the asset price in the stopping period. If the trading round continues beyond this period, the asset price still grows as before, but the true value of the asset stays at its maximum true value.

You will not learn right away when the true value has stopped growing. After the true value stops growing, you will only receive a message (notice), with a delay that is equally likely to be anywhere from 0 to 60 periods, indicating that the current price of the asset is above its true value. So you will never know the exact time period in which the true value stopped growing. A red arrow will indicate the period in which you have received that notice and that period will also be posted on the right-hand side of the screen (figure 6, 7).

The random delay between the time the true value stops growing and the message (notice) arrival is randomly chosen **separately** for each player. Therefore, when you receive your message, some players may have already received it, and some might not have received it yet. Also, all the messages are private, so you do not know when other players receive messages and they do not know when you received your message.

In each trading period, there is a 2.5% chance that the true value will stop growing (if it has not stopped already). This percentage is constant in each period, which implies that even if the round has just begun, there is a small (2.5%) chance it will end in the next period, and even if the round has lasted a long time, there is a small (2.5%) chance it will end in the next period.

At the end of each trading round, your earnings and the earnings of other players for this round will all be displayed on your screen (figure 8). Note that in this example, the 3 players who did not sell in time will receive the maximum true value of the asset ($3.20 in the sample screen in figure 8).

In each round, you will be grouped with 5 new computer players. They will receive the same amount of information as you do (though at a different time in regards to the maximum true value message). However, they will be playing with a predetermined strategy, which will remain consistent throughout the experiment, but unknown to you.

Static Trading Rounds

The static trading rounds are the same as the dynamic rounds with one difference: You are presented with your message, and with all of the other information that is revealed across time in the dynamic rounds, all at once (figure 9). More specifically, you get to step outside of time and see what the stock price would be at any time under the assumption that the market had not ended by that time. The period in which your message is received is shown with a red arrow; remember that the message is still randomly delayed from the time when the true value stopped growing. You then choose at what price along the curve you would sell (and the five computer players will be doing the same).

You can explore the stock price over time by moving a little blue bar on the screen (figure 10). Place a cursor on any point on the white bar below the x-axis of the price-period plot to move the blue bar. You do **NOT** have to hold a button on the mouse. The period and the price corresponding to the location of the blue bar will be automatically updated in the plot.

When you have determined the period in which (or the price at which) you want to sell your asset, press the ENTER key to submit your decision.

Once you submit your decision, the computer compares the selling times of all 6 players (you and 5 other computer players), and determines earnings as in a dynamic round. First, the computer calculates the time of the market ending as the time by which the first 3 players had sold. If your selling time is before the market ended, you will earn an amount equivalent to the asset price at which you sold. If your selling time is after that end time (i.e., three other players chose selling times earlier than yours), you earn the maximum true value of the stock as in the dynamic round.

To summarize:

1. You will be playing with 5 computer players (not other people in the room).
2. Only 3 players can sell their asset before the trading round ends.
3. In each trading round, the computer randomly chooses a period and the true value of the asset grows with the price up to this period. Afterwards, the price exceeds the true value.
4. Those 3 players who submit their decision in time will receive earnings equivalent to the asset price in the period in which they sold their asset. Others will receive the maximum true value of the asset.
5. In dynamic trading rounds, sellers make a real-time decision and will receive a message with a random delay after the true value has reached its maximum.
6. In static trading rounds, sellers learn when a message would have arrived (still with a random delay), had they played this round in real time, and you can make a selling decision without time pressure.

For you to become familiar with the software, we will ask you to complete 10 practice rounds (5 dynamic rounds followed by 5 static rounds). After completing the practice, you will go through 5 blocks of rounds with each block consisting of 10 dynamic rounds followed by 10 static rounds.

At the end of the experiment, we will sum up the money you earn in all trading rounds and pay you in cash. The conversion rate is 100 Experimental Dollars = 0.50 US Dollar. Your total earnings will be what you earned in the 100 rounds plus your show-up fee of $5. Are there any questions?

You can read these instructions again yourself until you understand how the experiment works. When you are ready, please complete the quiz and let the experimenter know when you are done.

Figures for the instructions

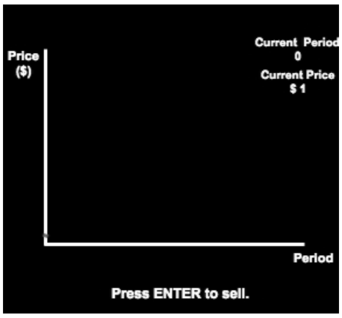

Figure A7: The start of a trading round.

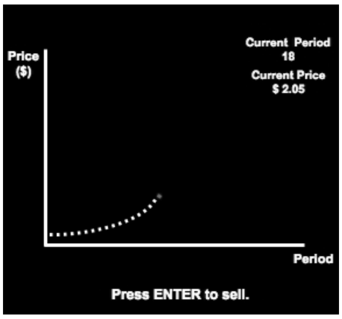

Figure A8: A trading round in action. The price grows exponentially.

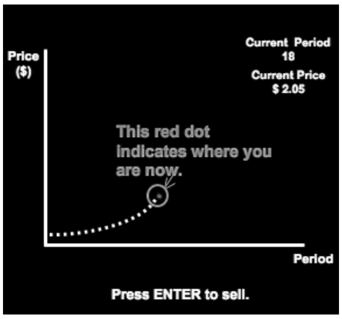

Figure A9:

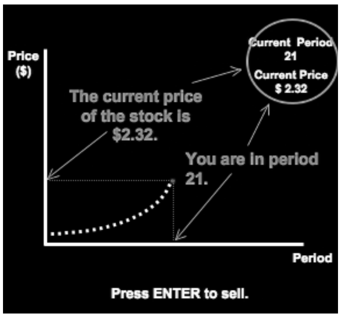

Figure A10:

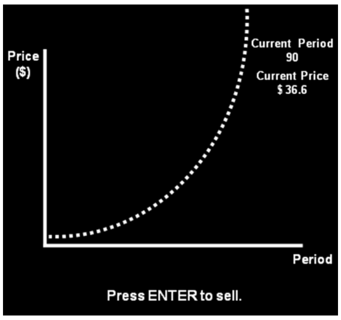

Figure A11: This is not an error.

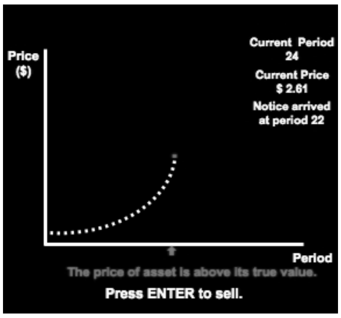

Figure A12: You will be notified that the true value has stopped growing already.

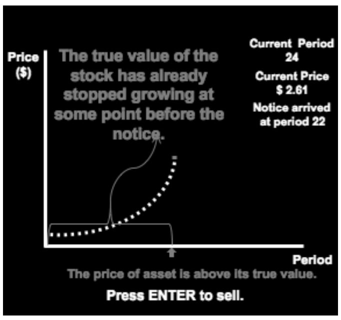

Figure A13: Note that the sentence in yellow will not appear in the actual screen.

Figure A14:

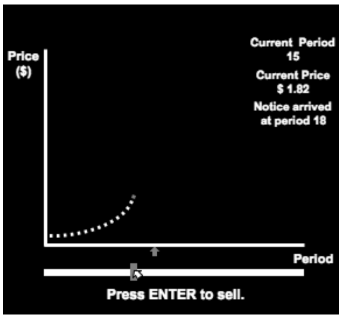

Figure A15: A static trading round.

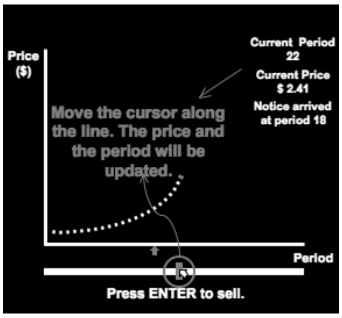

Figure A16: Explore the price in each period with the mouse before submitting your decision.

Quiz

Name:
Quiz
True or False

1. You are playing with other people in the room. (True, False)
2. The price of the asset increases at different rates in dynamic and static rounds. (True, False)
3. The price of the asset never decreases or stops. (True, False)
4. The maximum true value of the asset is the same as the asset price in the period when you receive a notice. (True, False)
5. The true value of the asset always matches the price. (True, False)
6. You earn the maximum true value of the asset when the market ends before you decide to sell. (True, False)
7. In static trading rounds, all players earn an amount equal to the price during the period in which they chose to sell. (True, False)
8. There is a 2.5% chance that the true value stops increasing in every period in static rounds. (True, False)
9. There is a 2.5% chance that the asset price stops increasing in every period in static rounds. (True, False)
10. All the players receive the notice that the true value stops growing, but at different time points. (True, False)
11. Your selling price is always greater than the true value of the asset. (True, False)
12. A trading round ends once three players sold their asset. (True, False)

Subject	Mean Dev	Anxiety	Learning Rate
1	22.32	0.08	0.16
2	6.51	0.10	0.20
3	7.46	0.07	0.14
4	6.71	0.09	0.18
5	9.41	0.10	0.20
6	7.51	0.09	0.18
7	5.54	0.07	0.14
8	4.98	0.04	0.08
9	9.95	0.10	0.20
10	8.26	0.07	0.14
11	5.79	0.06	0.12
12	56.16	0.00	0.00
13	6.65	0.10	0.20
14	6.39	0.10	0.20
15	34.98	0.00	0.00
16	6.62	0.10	0.20
17	8.17	0.10	0.20
18	7.67	0.09	0.18
19	7.04	0.07	0.14
20	11.47	0.09	0.18
21	7.75	0.10	0.20
22	4.46	0.10	0.20
23	8.50	0.09	0.18
24	7.18	0.10	0.20
25	7.00	0.10	0.20
26	6.60	0.10	0.20
27	7.71	0.08	0.16
28	4.80	0.10	0.20

Table A4: Best fit to the behavioral data for individual Caltech subjects.

Appendix .1. Tables for individual learning fits

Subject	Mean Dev	Anxiety	Learning Rate
1	5.92	0.09	0.18
2	9.20	0.04	0.08
3	6.08	0.08	0.16
4	25.07	0.04	0.08
5	8.08	0.04	0.08
6	11.19	0.06	0.12
7	13.30	0.10	0.20
8	8.63	0.07	0.14
9	8.40	0.04	0.08
10	26.38	0.00	0.00
11	42.54	0.00	0.00
12	6.13	0.04	0.08
13	14.74	0.09	0.18
14	11.45	0.06	0.12
15	8.82	0.07	0.14
16	11.56	0.06	0.12
17	7.66	0.07	0.14
18	19.58	0.00	0.00
19	7.45	0.03	0.06
20	5.06	0.09	0.18
21	11.01	0.06	0.12

Table A5: Best fit to the behavioral data for individual UCLA subjects.

3